

# **Socioeconomic inequity in the delivery of health care in England: accounting for vertical inequity**

**Laura Vallejo-Torres and Steve Morris,  
University College London  
Paper number P19**

## **ABSTRACT**

*Aims:* Most economic analyses of equity in health care utilisation focus on horizontal inequity. Underpinning these analyses is the assumption that the average effect of need on use is vertically equitable. We measure socioeconomic-related vertical equity in the use of health care in England and combine this with estimates of horizontal inequality to assess overall socioeconomic inequity.

*Data:* Data for the analysis were taken from up to five rounds of the Health Survey for England (1998-2002; n = 54,690).

*Methods:* Our measure of health is constructed using the predicted values from an interval regression of self-assessed health against a detailed set of health indicators. The measure has a maximum value of 1 (=full health) and values less than zero are worse than death. Similar methods are used to measure socioeconomic status. We compute indices of horizontal inequity for GP, inpatient and outpatient visits. Socioeconomic-related vertical equity is measured by generating a target relationship between health and use based on the relationship observed in (i) individuals with a health value higher than 0.5, and (ii) the richest 50% of the population.

*Results:* We found pro-poor horizontal inequity for GP visits and inpatient stays; outpatient visits are horizontally pro-rich. Vertical inequity estimates using both target functions are pro-rich for all types of use, making the overall socioeconomic inequity estimate of GP use pro-rich when imposing the effect of the richest 50%; inpatient stays remain pro-poor.

*Conclusions:* There is pro-rich vertical inequity for health service use. For GP and outpatients visits overall socioeconomic inequity is pro-rich while for inpatients stays it is pro-poor.

## **INTRODUCTION**

Most economic studies of equity in the delivery of health care have focused on the notion of 'equal treatment for equal need' which has been defined as *horizontal* equity in health care

utilisation. Using this concept, patients with equal needs for health care should receive the same treatment, irrespective of other characteristics such as income, race and place of residence (1-3). In empirical work, a concentration index approach has been used to measure horizontal inequity in health care use and a great deal of evidence regarding horizontal equity have been provided (e.g. 2, 4-10).

Very little attention in the literature has been paid to vertical equity in health care utilisation. Vertical equity is defined as the *appropriately* different treatment of individuals with different needs. This requires making strong value judgements about the way consumption ought to vary amongst individuals with different levels of need (11), and therefore most empirical work only considers horizontal inequity in health care utilisation.

A major limitation of concentrating solely on horizontal inequity is that it implies that the treatment received on average for individuals with the same needs is *appropriate*, and that deviations from this average treatment are only what matter. This assumption is made because horizontal equity is measured by comparing actual use with the average use received by individuals with the same needs across the whole population. This is similar to assuming that, 'on average the system gets it right' (2), which has been criticised, especially when comparisons across different countries or time periods are made (12). Analyses of horizontal inequity do not explore the assumption of how *appropriate* the average effect of need is on health care consumption, and hence these studies potentially ignore systematic unmet needs for some groups of the population.

Very few economic studies have attempted to test for or measure vertical equity in the distribution of health care. Abásolo et al (13), Liu et al (14), and Gravelle et al. (11) have tried to incorporate some assessment of vertical equity in their analyses by looking at the coefficients on the need variables included in their utilisation regression models used to test for horizontal inequity. They argue that a necessary condition for vertical equity is that individuals with greater needs should have greater health care utilisation. They found in most cases that this was the case. However, all these studies recognised that this is not a sufficient test for vertical equity because it cannot discern whether or not the higher utilisation by sick individuals compared with the healthy is appropriate for their greater needs.

A series of other papers looking at vertical equity have explored whether the difference between the treatment unequal individuals receive is affected by non-need variables (15-16). These focus on the effect of gender on patient admission to ICU care and cardiac rehabilitation at different levels of severity. The idea behind these analyses is that when, for example, no gender differences in utilisation are found after adjusting for needs this is often said to reflect fair health care use with respect to gender; but this *assumes* that at every level of need the gender difference in health service use is the same. This assumption is tested either by examining interactions between non-need and need variables or by stratifying analyses according to different levels of need and testing for different non-need effects. However, Wagstaff et al., 1991b also suggested looking at the interaction between needs and a non-need variable (e.g., income) to test for *horizontal* inequity, arguing that if ill individuals when they are rich receive more health care than the poor, the principle of ‘equal treatment for equal needs’ is not met. As Gravelle et al. 2006 point out, if the effect of morbidity on use varies across income groups this cannot be separated easily into horizontal and vertical aspects. Hence, this approach cannot be used as a direct test for vertical equity.

In their review of the health care resource allocation formula for Scotland, Sutton and Lock, 2001 (17), explore the implications of including a vertical equity objective. They ran utilisation models on only the most ‘responsive’ areas (those that allocated proportionally more resources to individuals with higher needs), and compared the resulting NHS allocations to those that would be achieved using a similar model across all areas. This approach was also adopted in similar reviews in England (18-19).

Using individual health survey data, Sutton (2002) provides a framework for disentangling the vertical and the horizontal components of socioeconomic inequity in GP contacts in Scotland. This is the first attempt to measure the extent to which the divergence between a target allocation of health care and the allocation that results after standardising for the average effect of needs variables falls disproportionately on the poor. In this paper, the target allocation is created by imposing a linear and positive relationship between levels of morbidity and utilisation found at low level of need to the whole sample. The analysis revealed pro-rich estimates of horizontal and vertical inequity of GP visits.

Sutton, 2002, provides the most comprehensive exploration of the vertical aspects of socioeconomic inequity in health care use to date. In this paper we use a similar approach to

quantify horizontal and vertical components of health care utilisation in England. We extend the analysis by looking at different types of health contacts (GP visits, inpatient stays, outpatient visits), and by exploring alternative target allocation functions of health care use based on the relationship observed in relatively healthy individuals and in the richest half of the population.

## **METHODS**

### *Data*

The analysis of GP visits is based on data from five rounds (1998-2003) of the *Health Survey for England* (HSE). The analysis of inpatient stays and outpatient visits is based on three rounds (1998-2000). The HSE is a cross-sectional representative national survey which draws a different sample every year of individuals living in England. Respondents are interviewed on a range of topics including their age, their socioeconomic status, their health status, and health care utilisation. We excluded individuals under the age of 16 years whose data for some variables were not available.

### *Measurement of health*

We follow Sutton, 2002 and use the method proposed by van Doorslaer and Jones, 2003 (20) to construct a continuous health measure. Respondents' self-assessed health (SAH), based on responses to the question: 'How is your health in general? Would you say it was... very good, good, fair, bad or very bad?') is regressed against age, gender and a detailed set of health indicators using an interval regression model. The cut-points for the model were computed using information on the empirical distribution of EQ-5D scores ([www.euroqol.org](http://www.euroqol.org)) and mapping these to the cumulative frequency of the SAH categories. Information on the empirical distribution of EQ-5D scores was not available for 1998-2002 so we used EQ-5D data for 2003-2006. Using these data, the cumulative percentages of individuals reporting very bad, bad, fair and good health in our sample were 1.4%, 6%, 23.4%, and 66.1%, respectively; and the corresponding values from the empirical distribution of EQ-5D values was -0.003, 0.516, 0.796, and 1.000, respectively. Using these cut-points we then regressed the SAH variable against the regressors and we predicted health status for every individual observation in the pooled dataset based on the resulting coefficients. The predictions provide a continuous health variable with an upper bound of unity (representing

full health). Values of zero are equivalent to death and negative values represent health states worse than death.

#### *Measurement of socioeconomic status*

We also used an interval regression approach to construct a continuous socioeconomic measure that summarises in a single index different aspects of the socioeconomic circumstances of the individual. We regressed household income reported in 31 income bands against a set of individual and household characteristics. We made out of sample predictions from this model that allowed us to impute the socioeconomic status variable for individuals who did not report their household income (around 18% of the sample).

#### *Measurement of inequity*

We use a concentration index approach to quantify socioeconomic-related inequity in health care (1,3). In Figure 1 individuals are ranked along the  $x$ -axis according to their socioeconomic status. Against this, the cumulative proportion of the health care received by each individual is plotted. The solid line  $CC_{\text{actual}}$  is the concentration curve of actual use which will lie above (below) the line of equality if poorer (richer) individuals receive more than proportional health care. We compare this curve with the curve of need-predicted health care use to compute the horizontal inequity estimate. The need-predicted curve is derived from a regression model of health care against need and non-need variables. Suppose the following utilisation equation

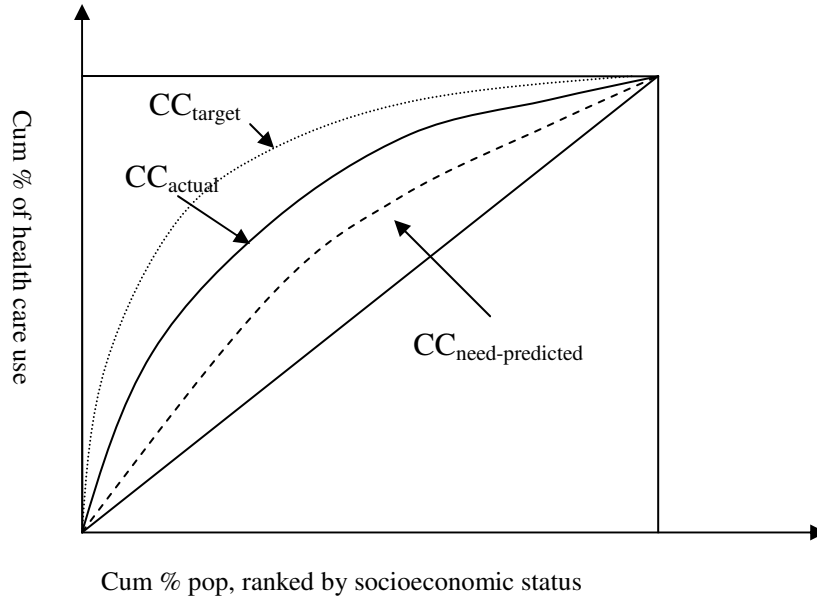
$$\hat{q}_i = \hat{\alpha} + \hat{\beta}N_i + \hat{\delta}\bar{Y}_i + \varepsilon_i \quad (1)$$

Where  $q_i$  measures health care consumption;  $N_i$  is a set of needs variables and  $Y_i$  is a set of non-needs variables. The effect of the non-need variables are neutralised by setting them equal to their means. Equation (1) can be used to predict how much health care individuals would have received if they had been treated as others with the same need characteristics were, on average, treated in the system. This is illustrated in Figure 1 by the dashed line  $CC_{\text{need-predicted}}$ . When the concentration curve of actual use lies below (above) the concentration curve of need-predicted use, there is horizontal inequity favouring the rich (poor). The inequity can then be quantified by the concentration coefficient, measured as twice the area between the need-predicted and the actual concentration curves:

$$HI = 2 * \int [L_{need-predicted} - L_{actual}] = CI_{actual} - CI_{need-predicted} \quad (2)$$

Recognising that the way individuals at different level of needs are treated on average in the system may not reflect their differences in need, we compare the need-predicted curve with the curve resulting from a target distribution of health care (dotted line  $CC_{target}$  in Figure 1) to compute the estimate of socioeconomic vertical equity.

**Figure 1. Concentration curves of actual, need-predicted and target utilisation with respect to income**



The target is summarised by Equation (3)

$$q_i^* = \alpha^* + \beta^* N_i + \delta^* \bar{Y}_i + \varepsilon_i \quad (3)$$

The effect of the need variables from Equation (3) are estimated by imposing a restriction on the health-health care utilisation relationship. We impose two separate targets. The first is the health-health care utilisation relationship in individuals with a health measure higher than 0.5. The second is the relationship in the richest 50% of the population as measured by our predicted socioeconomic variable. The justification for using the first target function is that we find for individuals at very low levels of health, either that the effect of health on health

care use is positive (i.e., relatively healthy individuals in low health groups receive more health care than relatively sick individuals) or constant, depending on the type of use, suggesting that there are unmet needs for individuals at the lowest levels of health. For consistency, we applied the same cut point to each measure of health care use; we use the effects of individuals with a health value higher than 0.5. This represents about 97% of the sample. The justification for using the second target function (based on the richest 50% of the population) is that evidence suggests that the more well-off individuals are less likely to have unmet needs (e.g. 21-24), partly because they are more easily able to overcome financial or administrative barriers to accessing health care; and partly because they are more aware of the marginal benefits of health care consumption.

Socioeconomic-related vertical equity is then measured as the difference between need-predicted and target health care with respect to income. When the concentration curve of need-predicted use lies below (above) the concentration curve of target use, there is vertical inequity favouring the rich (poor). Analogous to horizontal equity, we quantify vertical equity as twice the area between the target and the need-predicted concentration curves:

$$VI = 2 * \int [L_{target} - L_{need-predicted}] = CI_{need-predicted} - CI_{target} \quad (4)$$

The overall socioeconomic inequity in health care is the sum of the vertical and horizontal inequity estimates (12).

#### *Models for utilisation of health care*

We compute estimates of horizontal and vertical socioeconomic inequity for the number of GP visits in the last two weeks, and for the probability of inpatient stays and outpatient visits in the last 12 months. We regress each type of contact against age (a cubic function), gender, interactions between age and gender, our health measure (specified as a polynomial function to up to the fifth-order according to the joint significance of the power terms) and our measure of socioeconomic status. We also control for year of data, and Government Office Region (GOR) of residence of the individual. To account for the non-linear nature of the dependent variables, GP visits are estimated using a negative binomial model, and inpatient and outpatient probabilities are estimated using probit regression models.

### *Sampling issues*

All models use sample weights and are adjusted for clustering at the Primary Sample Unit level. To maximise the sample size we imputed missing values. Missing values for income were imputed using the prediction from an interval regression model of income on the other covariates as explained above. For binary and categorical variables, missing values were assigned to the omitted category. To allow for the possibility that items were not missing at random we included dummy variable for all imputed items to indicate item non response. All analyses were undertaken using Stata version 10.

## **RESULTS**

The sample size for the analysis of GP visits (inpatient stays and outpatient visits) is 54,690 (31,926) observations. The mean number of GP visits was 0.19 (range 0-9; % <1 =83.9%). The proportion of the sample who had an inpatient stay in the previous 12 months was 0.10; the proportion who had an outpatient visit was 0.33. Summary statistics of the variables included in the models of health and socioeconomic status are in Tables 1-2.

Table 1 shows the results of the interval regression model of self-assessed general health. Age has a non-linear effect on health that does not vary significantly with gender, conditional on the other variables. The following indicators of ill health are negatively correlated with SAH: higher GHQ-12 scores, number of days cut down on normal activities due to illness or disability; number of longstanding illnesses, suffering from a limiting longstanding illness; being smoker; and having a body mass index (BMI) value outside the healthy range 20 to 25. Most of the reported longstanding illnesses also affect negatively SAH with the exception of eye, ear and skin complaints.

Table 2 presents the results of the interval regression of household income. Most variables have the expected sign, with lower social class, less education, minority ethnic groups, and economic activity other rather than being in paid employment all being negatively correlated with household income. Owning a house is positively correlated with income as compared with the other tenure status with the exception of buying a house with the help of a mortgage. The number of cars and bedrooms in the household, and being married are also positively correlated with household income.

### *GP visits*



The models for GP visits are in Table 3. We found a pro-poor estimate of horizontal inequity (-0.082), indicating that after controlling for differences in needs (based on the average effect across the whole population), the poor receive proportionally more GP visits than the rich.

We show the effect of health and age on GP visits based on the coefficients from the regression models for the total population and for the two subgroups graphically in Figure 2. All the other variables are held constant at their sample means. We found that, for the whole sample, the number of GP visits increases as health status declines but the effect becomes flatter at low levels of health; individual age does not affect GP visits at any level of health status conditional on predicted health status (which is estimated as a function of age). Using the coefficients from the model run only on individuals with health >0.5, the predicted number of visits for individuals increases with declining health status across the whole distribution, except at very low health status. When we use the coefficients for the richest 50% of the population use increases with declining health across the whole distribution. The partial effects of health, and age (by gender groups) in the three models are presented in Figure 2d-2f, for ease of comparison.

Using both target functions we found pro-rich estimates of socioeconomic vertical inequity, i.e., the divergence between need-predicted and target health care use falls disproportionately on the poor (Table 3). The estimate is bigger using the target function from the richest 50% of the population (0.096). The overall estimate of socioeconomic inequity remain pro-poor when the target is set by the effect of the individuals with a predicted health value higher than 0.5, but becomes pro-rich when the effect of the need variables of the richest 50% is imposed as the target, although the latter is not statistically significant.

### *Inpatient stays*

We also found a pro-poor estimate of horizontal inequity for inpatient stays (-0.050), see Table 4. The effect of the need variables on inpatient stays are presented in Figure 3. The average effect for the whole population shows that the probability of an inpatient stays is negatively correlated with health status for most of the health distribution, but it becomes positive at low levels of health. Age has a positive effect on inpatient stays after controlling for health status, which is itself a function of age. For individuals with health >0.5, and for the richest 50%, the probability of inpatient stay increases with ill health across the whole health distribution, and the predicted probability at older ages is higher (see Figures 3a-3c). Figures

3e and 3f show that the effect of old age among the richer population is mainly driven by the higher probabilities experienced by females.

We found pro-rich estimates of vertical inequity using both target functions (0.009 and 0.047), and the overall estimates of socioeconomic inequity are pro-poor irrespective of the target function (Table 4), but it is not statistically significant using the target based on the richest 50%.

### *Outpatient visits*

Table 4 also show the results of the models for the probability of an outpatient visit. In this case, the estimate of horizontal inequity is pro-rich (0.019), suggesting that rich individuals receive more outpatient visits after controlling for the average effect of the need variables. These effects are presented in Figure 4a. Similarly with the inpatient stays, we found that outpatient probability increases with ill health for most of the health range, but decreases at low level of health status. The effect of age is less pronounced than in the case of inpatient visits. Figures 4b and 4c show the effect for the healthier and the richer, respectively. Again, in these groups the probability increases with declining health across the whole distribution. The effect of age is greater in the richest 50% of the population sample, in this case, this is due to the increased probability among males (see Figures 4e-4f).

The vertical equity estimates are presented in Table 4. Under both targets the vertical inequity estimates are pro-rich, and the overall estimate of socioeconomic inequity is also pro-rich.

## **DISCUSSION**

In this paper we have explored the horizontal and vertical components of socioeconomic-related inequity in the delivery of health care in England. We found that using the standard analysis of inequity that overlooks vertical inequity aspects, GP visits and inpatient stays were concentrated among the poor after controlling for the average effect of needs. Outpatient visits were horizontally pro-rich.

Studies of horizontal inequity implicitly assume that the average effects of the need variables appropriately reflect differences in needs. This is problematic because, for example, individuals in greater needs may systematically underuse health care, as described by

“inverse care law” (25) (“*the availability of good medical care tends to vary inversely with the need for it in the population served*”). The finding that individuals in greater need consume less health care may be related with the fact that greater needs are more common among the lower socioeconomic groups and such groups may experience different marginal utilities of health care consumption (26). Individuals in higher socioeconomic groups may need less time to access health care (e.g., with better transport and medical facilities) and are less likely to lose income for the time spent consuming health care. Additionally, the marginal valuation of the benefit of health care may be higher if they perceive health care as contributing to their improvement in health.

Estimating a target for health care use implies making strong value judgments about the appropriate effect of need variables on health care use. In our study, we used the effect found in two subgroups of the population; those with a health measure higher than 0.5, and that of the richest 50% of the population. The justification for choosing these target functions is based on both theoretical and ex-post findings that these groups are less likely to be affected by unmet needs. We found that, for all types of use, the divergence between need-predicted and target health care use falls disproportionately on the poor. This is because when using a target based on the healthy or the rich, the less healthy ought to receive more health care, and the less healthy are concentrated among the poor.

When we combined the estimates of horizontal and vertical inequity, the overall estimate of inequity becomes pro-rich and non-significant for GP visits using the target based on the richest 50% of the population. Inpatient estimates are pro-poor but the estimate of overall inequity is substantially reduced compared with the horizontal inequity index, and became non-significant when imposing the effect of the relatively richer. The total inequity estimate of outpatient visits becomes even more pro-rich when accounting for vertical inequity. This suggests that focusing on horizontal inequity alone gives a misleading picture of overall inequity.

Further work will focus on exploring the extent in which the divergence between actual health care use and target health care use varies across the health distribution. This will shed more light on the issue of vertical inequity by identifying the groups across the health distribution receiving proportionally less health care than appropriate to account for differences in needs.

## REFERENCES

1. Wagstaff, Paci and Van Doorslaer, On the measurement of inequalities in health, *Social Science and Medicine* 33 (1991), pp. 545–557.
2. Van Doorslaer *et al.*, Equity in the delivery of health care in Europe and the US, *Journal of Health Economics* 19 (5) (2000), pp. 553–5833
3. Wagstaff and Van Doorslaer, Equity in health care finance and delivery. In: A.J. Culyer and J.P. Newhouse, Editors, *Handbook of Health Economics*, North-Holland (2000), pp. 1803–1862.
4. Wagstaff, Paci and Van Doorslaer, Horizontal equity in the delivery of health care, *Journal of Health Economics* 10 (1991b), pp. 251–256
5. Wagstaff and Van Doorslaer, Measuring and testing for inequity in the delivery of health care, *Journal of Human Resources* 35 (4) (2000), pp. 716–733.
6. Van Doorslaer, Koolman and Jones, Explaining income-related inequalities in doctor utilisation in Europe, *Health Economics* 13 (2004), pp. 609–628.
7. Van Doorslaer, Masseria, Koolman and the OECD Health Equity Group, Inequalities in access to medical care by income in developed countries, *Canadian Medical Association Journal* 174 (2006), pp. 177–183.
8. Bago d’Uva, T., Jones, A. Health care utilisation in Europe: new evidence from the ECHP. HEDG Working Paper 06/09, (2006). University of York.
9. Lu, Leung, Kwon, Tin, Doorslaer and O’Donnell, Horizontal equity in health care utilisation—evidence from three high-income Asian economies, *Social Science and Medicine* 64 (1) (2007), pp. 199–212.
10. Bago d’Uva, Jones, and van Doorslaer, Measurement of horizontal inequity in health care utilisation using European panel data, *Journal of Health Economics* 28 (2009), pp. 280–289.
11. Gravelle, Morris, and Sutton, Economic Studies of equity in the consumption of health care. In: *Elgar Companion to Health Economics*. Jones, A.M. (ed). Edward Elgar. (2006).
12. Sutton. Vertical and horizontal aspects of socio-economic inequity in general practitioner contacts in Scotland, *Health Economics* 11 (6) (2002), pp. 537-549.
13. Abásolo, Manning and Jones, Equity in utilization of and access to public-sector GPs in Spain, *Applied Economics* 33 (3) (2001), pp. 349-364.
14. Liu, Zhao, Cai, Yamada, and Yamad, Equity in health care access to: Assessing the urban health insurance reform in China, *Social Science and Medicine* 55 (10) 2002, pp. 1779-1794.

15. Raine, Goldfrad, Rowan and Black. Influence of patient gender on admission to intensive care, *Journal of Epidemiology and Community Health* 56 (6) (2002), pp. 418-423.
16. Raine, Hutchings, and Black. Is publicly funded health care really distributed according to need? The example of cardiac rehabilitation in the UK, *Health Policy* 63 (1) (2003), pp. 63-72.
17. Sutton and Lock. Regional differences in health care delivery: Implications for a national resource allocation formula, *Health Economics* 9 (2001), pp. 547–559
18. Sutton, Gravelle, Morris, Leyland, Windmeijer, Dibben, Muirhead. Allocation of Resources to English Areas; Individual and small area determinants of morbidity and use of healthcare resources. Report to the Department of Health. Edinburgh: Information and Statistics Division, 2002
19. Morris, Car-Hill, Dixon, Law, Rice, Sutton, Vallejo-Torres. Combining Age-related and Additional Needs; review of the needs formulae for hospital services and prescribing activity in England. Report to the Department of Health. London: Department of Health, 2007.
20. Van Doorslaer, and Jones. Inequalities in self-reported health: validation of a new approach to measurement, *Journal of Health Economics* 22 (1) (2003), pp. 61-78.
21. Agabiti, Picciotto, Cesaroni, et al. The influence of socioeconomic status on utilisation and outcomes of elective total hip replacement: a multicity population-based longitudinal study, *International Journal of Quality in Health Care* 19 (2007), pp. 37-44
22. Milner, Payne, Stanfield, et al. Inequalities in accessing hip joint- replacement for people in need, *European Journal of Public Health* 14 (1) (2004), pp. 58-62
23. Westin, Ahs, Persson, and Westerling. A large proportion of Swedish citizens refrain from seeking medical care – Lack of confidence in the medical services a plausible explanation? *Health Policy* 68 (3) (2004), pp. 333-344
24. Kirby and Kaneda. Neighbourhood socioeconomic disadvantage and access to health care, *Journal of Health and Social Behaviour* 46 (1) (2005), pp. 15-31
25. Hart. The inverse care law, *Lancet* 27 (7696) (1971), pp. 405-12.
26. Le Grand. The Distribution of Public Expenditure: The Case of Health Care, *Economica* 45 (178) (1978), pp.125-142

**Table 1. Interval regression model of self-assessed general health on set of health indicators**

	Mean	SD	Coeff	t		Mean	SD	Coeff	t
Female	0.548	0.498	0.015	0.88	Genito-urinary	0.022	0.147	-0.033	-3.75
Age	0.481	0.190	0.533	5.02	Musculo-skeletal	0.197	0.398	-0.013	-4.18
Age-squared	0.267	0.193	-1.220	-5.02	Skin complaints	0.019	0.137	0.012	1.65
Age-cubed	0.164	0.166	0.724	4.26	Other complains	0.002	0.039	-0.043	-1.69
Female*age	0.266	0.280	-0.091	-0.68	<b>Acute ill health</b>				
Female*age-squared	0.149	0.199	0.238	0.77	0 days	0.830	0.376		Base category
Female*age-cubed	0.093	0.152	-0.151	-0.7	1-3 days	0.048	0.214	-0.015	-4.53
<b>GHQ-12 score</b>					4-6 days	0.027	0.161	-0.038	-6.04
0	0.549	0.498			7-13 days	0.028	0.166	-0.062	-9.63
1	0.130	0.336	-0.022	-9.95	14 days	0.067	0.250	-0.125	-21.53
2	0.073	0.261	-0.035	-11.79	<b>Number of longstanding illnesses</b>				
3	0.046	0.209	-0.047	-11.45	0	0.546	0.498		
4	0.032	0.176	-0.057	-10.59	1	0.278	0.448		Base category
5	0.024	0.154	-0.076	-11.25	2	0.118	0.322	-0.031	-6.69
6	0.019	0.137	-0.079	-10.91	3	0.041	0.199	-0.088	-10.4
7	0.016	0.124	-0.086	-10.09	4 or more	0.017	0.131	-0.141	-10.09
8	0.012	0.111	-0.109	-10.64	<b>Limiting longstanding illness</b>				
9	0.011	0.102	-0.113	-10.4	Yes	0.268	0.443	-0.124	-41.37
10	0.010	0.101	-0.131	-10.78	<b>Smoking status</b>				
11	0.009	0.093	-0.137	-10.67	Non-smoker	0.412	0.492		Base category
12	0.009	0.094	-0.182	-12.51	Ex smoker	0.057	0.232	0.002	0.72
<b>Longstanding illnesses</b>					Ex-smoker regular	0.258	0.438	-0.005	-2.49
Infectious disease	0.002	0.046	-0.062	-2.03	Smoker	0.254	0.435	-0.040	-21.31
Neoplasms & benign	0.017	0.130	-0.086	-8.09	<b>Obesity</b>				
Endocrine & metabolic	0.057	0.231	-0.042	-8.64	BMI 20 to 25	0.306	0.461		Base category
Blood & related organs	0.006	0.079	-0.036	-2.59	BMI under 20	0.049	0.215	-0.016	-4.85
Mental disorders	0.028	0.166	-0.046	-6.4	BMI 25 to 30	0.341	0.474	-0.002	-1.33
Nervous system	0.039	0.193	-0.042	-7.01	BMI 30 to 35	0.134	0.341	-0.023	-9.16
Eye complaints	0.026	0.160	0.014	1.78	BMI 35 to 40	0.038	0.191	-0.040	-9.18
Ear complaints	0.026	0.159	0.018	2.63	BMI more than 40	0.013	0.114	-0.064	-8.25
Heart & circulatory	0.124	0.329	-0.061	-16.3	Constant			0.913	64.68
Respiratory system	0.093	0.291	-0.042	-12.28	N			55,615	
Digestive system	0.050	0.217	-0.045	-8.68	Adjusted R <sup>2</sup>			0.359	

All models control for year of data, and missing values. Sample weights are used and we adjust for clustering at Primary Sample Unit level.

**Table 2. Interval regression model of household income on individual and household characteristics**

	Mean	SD	Coeff	t		Mean	SD	Coeff	t
Female	0.548	0.498	-4669.2	-2.02	<b>Ethnic group</b>				
Age	0.481	0.190	6952.9	0.48	White	0.933	0.251	Base category	
Age-squared	0.267	0.193	-29059.5	-0.97	Black Caribbean	0.011	0.104	-3139.3	-3.69
Age-cubed	0.164	0.166	14729.4	0.75	Black African	0.007	0.083	-6363.1	-5.95
Female*age	0.266	0.280	30060.2	1.83	Black Other	0.001	0.030	-1160.1	-0.44
Female*age-squared	0.149	0.199	-62855.8	-1.77	Indian	0.016	0.124	-3723.3	-5.07
Female*age-cubed	0.093	0.152	41456.7	1.76	Pakistani	0.009	0.096	-6070.3	-5.87
<b>Social class of head of household</b>					Bangladeshi	0.005	0.070	-7350.5	-4.82
Professional	0.066	0.249	Base category		Chinese	0.002	0.049	-1841.0	-0.94
Managerial/technical	0.302	0.459	-3567.8	-9.71	Other	0.014	0.117	-3035.9	-4.02
Skilled non-manual	0.144	0.351	-12118.9	-28.75	<b>Number of cars in household</b>				
Skilled manual	0.266	0.442	-13190.4	-33.35	No car	0.216	0.412	Base category	
Semi-skilled manual	0.143	0.350	-13538.0	-31.2	One	0.439	0.496	1922.4	7.25
Unskilled manual	0.049	0.216	-14267.9	-25.98	Two	0.279	0.448	11126.8	35.08
Other	0.028	0.164	-11449.5	-16.83	Three or more	0.065	0.247	24179.6	54.1
<b>Economic activity</b>					<b>Bedrooms per person</b>	1.284	0.677	1307.2	8.18
In paid employment	0.525	0.499	Base category		<b>Marital status</b>				
Going to school/college full	0.044	0.205	110.8	0.22	Married	0.556	0.497	Base category	
Permanent long term sickness	0.041	0.198	-7472.3	-16.59	Single	0.231	0.422	-4124.5	-14.05
Retired from paid work	0.235	0.424	-6843.0	-18.48	Separated	0.025	0.155	-5958.5	-10.6
Looking after the home	0.108	0.311	-3858.4	-12.17	Divorced	0.077	0.266	-4759.1	-13.82
Waiting to take up paid job	0.002	0.049	-4336.5	-2.53	Widowed	0.095	0.294	-2910.2	-6.91
Looking for paid job	0.019	0.138	-8626.6	-13.92	<b>Tenure</b>				
Temporary sickness or injury	0.003	0.059	-8599.7	-6.17	Own	0.296	0.456	Base category	
Doing something else	0.004	0.064	-6722.9	-4.99	Mortgage	0.436	0.496	3754.6	14.65
<b>Education</b>					Part mortgage	0.005	0.069	-3804.3	-3.17
Degree	0.138	0.345	Base category		Rent	0.250	0.433	-2301.2	-7.94
Higher education less than	0.106	0.308	-8539.2	-24.31	Free rent	0.011	0.104	-3803.1	-3.96
A level or equivalent	0.107	0.309	-7598.4	-21.46					
GCSE or equivalent	0.223	0.416	-9230.4	-29.68	$\sigma$			18126.8	61.05
CSE or equivalent	0.053	0.225	-10483.6	-22.77					
Other qualification	0.047	0.212	-9625.8	-19.57	N	45,546			
No qualification	0.308	0.462	-9937.5	-29.04	Adjusted R <sup>2</sup>	0.074			

All models control for year of data, GOR of residence and missing values. Sample weights are used and we adjust for clustering at Primary Sample Unit level.

**Table 3. Negbin models of GP visits (for all population, sample truncated at health>0.5 and richest 50% of the sample)**

	All		Truncated h>0.5		Richest 50%	
	Coeff	z	Coeff	z	Coeff	z
Health	-30.636	-1.78	27.123	0.37	9.083	0.2
Health <sup>2</sup>	136.304	2.13	-89.157	-0.6	-31.919	-0.2
Health <sup>3</sup>	-282.748	-2.49	109.443	0.83	29.700	0.11
Health <sup>4</sup>	269.423	2.81	-47.899	-1.1	2.051	0.01
Health <sup>5</sup>	-97.583	-3.14			-11.284	-0.17
Female	0.430	1.3	0.321	0.94	0.110	0.19
Age	-0.609	-0.34	-1.067	-0.56	1.726	0.55
Age-squared	1.891	0.51	2.852	0.72	-4.411	-0.66
Age-cubed	-1.349	-0.58	-1.936	-0.77	3.687	0.83
Female*age	2.638	1.19	3.519	1.52	5.117	1.25
Female*age-squared	-8.303	-1.83	-10.161	-2.13	-14.205	-1.57
Female*age-cubed	5.442	1.88	6.613	2.17	9.969	1.6
Socioeconomic status	-0.00001	-5.4	-0.00001	-5.58	-0.000002	-0.95
$\alpha$ (standard deviation)	0.393 (0.044)		0.424 (0.050)		0.436 (0.072)	
N	54,690		53,052		27,247	
Adjusted R <sup>2</sup>	0.070		0.060		0.061	
Test: $h=h^2=h^3=h^4=h^5=0$	2752.68	<0.0001	2038.09 <sup>a</sup>	<0.0001	1493.78	<0.0001
Test: $h^2=h^3=h^4=h^5=0$	284.6	<0.0001	156.7 <sup>b</sup>	<0.0001	105.87	<0.0001
<b>HI</b>	-0.0815	-5.97				
<b>VI</b>			0.0319	21.67	0.0963	41.89
<b>TI</b>			-0.0496	-3.60	0.0148	1.06

All models control for year of data, GOR of residence and missing values. Sample weights are used and we adjust for clustering at Primary Sample Unit level.

<sup>a</sup> Test:  $h=h^2=h^3=h^4=0$ ; <sup>b</sup> Test:  $h^2=h^3=h^4=0$

HI: horizontal inequity; VI: vertical inequity; TI: total inequity



**Table 4. Probit models of inpatient and outpatient probability (for all population, sample truncated at health>0.5 and richest 50% of the sample)**

	Inpatient probability						Outpatient probability					
	All		Truncated h>0.5		Richest 50%		All		Truncated h>0.5		Richest 50%	
	Coeff	z	Coeff	z	Coeff	z	Coeff	z	Coeff	z	Coeff	z
Health	12.001	0.6	-2.441	-26.58	-2.246	-16.75	26.754	1.32	-45.146	-0.77	-39.487	-1.69
Health <sup>2</sup>	-47.929	-0.66					-105.098	-1.48	94.047	0.81	84.478	1.63
Health <sup>3</sup>	84.735	0.67					183.469	1.54	-88.476	-0.87	-80.894	-1.63
Health <sup>4</sup>	-74.746	-0.72					-153.232	-1.59	29.984	0.9	27.596	1.58
Health <sup>5</sup>	25.566	0.78					48.752	1.63				
Female	-0.681	-2.41	-0.696	-2.42	-2.438	-5.21	-0.570	-2.7	-0.547	-2.58	-0.190	-0.56
Age	-2.744	-1.77	-2.607	-1.66	-3.896	-1.47	-3.637	-3.25	-3.601	-3.18	-1.881	-1.03
Age-squared	4.341	1.34	3.918	1.19	7.872	1.33	5.677	2.34	5.583	2.27	-0.179	-0.04
Age-cubed	-1.266	-0.6	-0.906	-0.42	-3.925	-0.95	-2.601	-1.61	-2.547	-1.55	2.723	0.9
Female*age	8.110	4.15	8.200	4.1	21.437	6.21	2.122	1.42	1.934	1.28	-1.413	-0.56
Female*age-squared	-18.759	-4.56	-18.774	-4.46	-48.982	-6.26	-1.892	-0.59	-1.518	-0.47	7.956	1.36
Female*age-cubed	11.672	4.38	11.558	4.22	32.480	5.94	0.029	0.01	-0.152	-0.07	-8.045	-1.92
Socioeconomic status	-0.000004	-4.55	-0.000004	-4.45	-0.000003	-1.67	0.0000003	0.43	0.0000003	0.39	-0.000001	-0.59
N	31926		30990		15963		31930		30994		15965	
Adjusted R <sup>2</sup>	0.087		0.071		0.055		0.073		0.059		0.05	
Test h=h <sup>2</sup> =h <sup>3</sup> =h <sup>4</sup> =h <sup>5</sup> =0	956.81	<0.0001					2251.73	<0.0001	1476.8 <sup>a</sup>	<0.0001	733.71 <sup>a</sup>	<0.0001
Test h <sup>2</sup> =h <sup>3</sup> =h <sup>4</sup> =h <sup>5</sup> =0	10.86	0.028					31.99	<0.0001	16.04 <sup>b</sup>	0.0011	13.36 <sup>b</sup>	0.0039
<b>HI</b>	-0.0499	-5.41					0.0191	1.36				
<b>VI</b>			0.0090	21.50	0.0466	21.37			0.0078	18.77	0.0552	41.97
<b>TI</b>			-0.0410	-4.44	-0.0053	-0.56			0.0268	1.90	0.0743	5.26

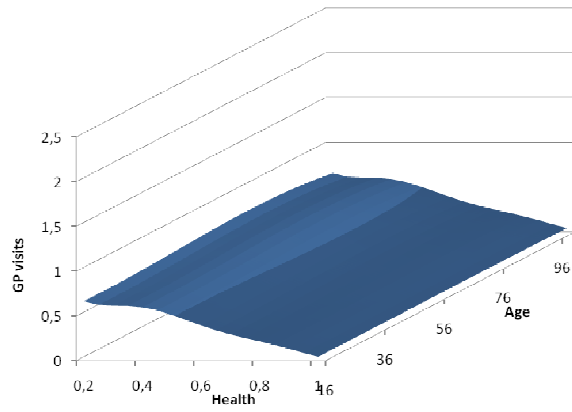
All models control for year of data, GOR of residence and missing values. Sample weights are used and we adjust for clustering at Primary Sample Unit level.

<sup>a</sup> Test: h=h<sup>2</sup>=h<sup>3</sup>=h<sup>4</sup>=0; <sup>b</sup> Test: h<sup>2</sup>=h<sup>3</sup>=h<sup>4</sup>=0

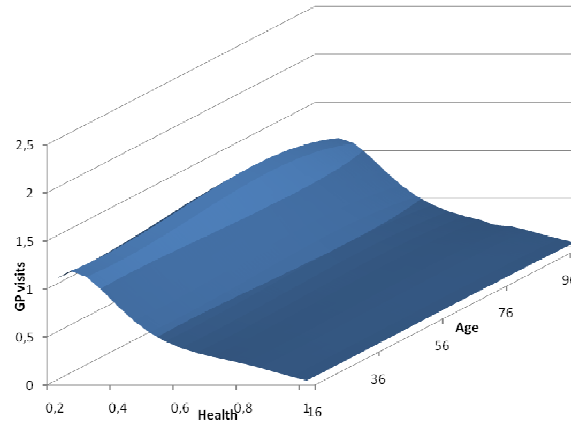
HI: horizontal inequity; VI: vertical inequity; TI: total inequity

**Figure 2. Effect of need variables on GP visits (for all population, sample truncated at health>0.5 and richest 50% of the sample)**

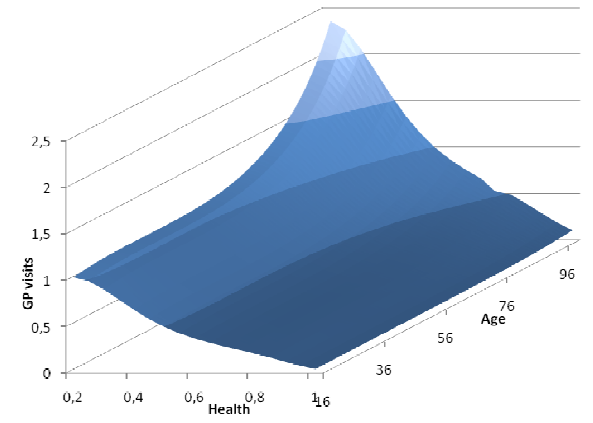
**2(a) All**



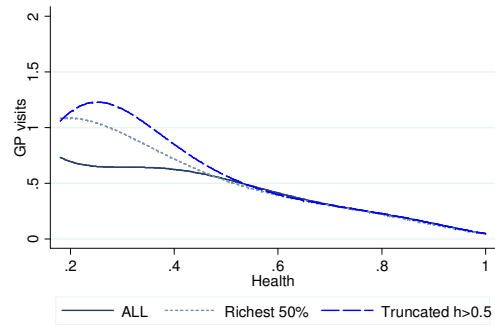
**2(b) Truncated h>0.5**



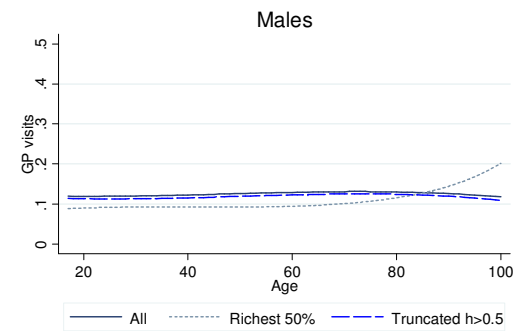
**2(c) Richest 50%**



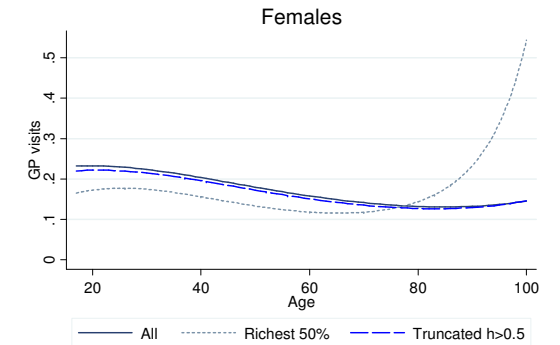
**2(d) Average partial effect of health**



**2(e) Average partial effect of age (Males)**

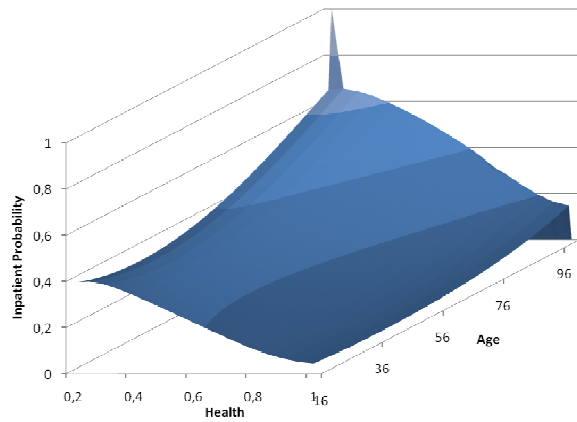


**2(f) Average partial effect of age (Females)**

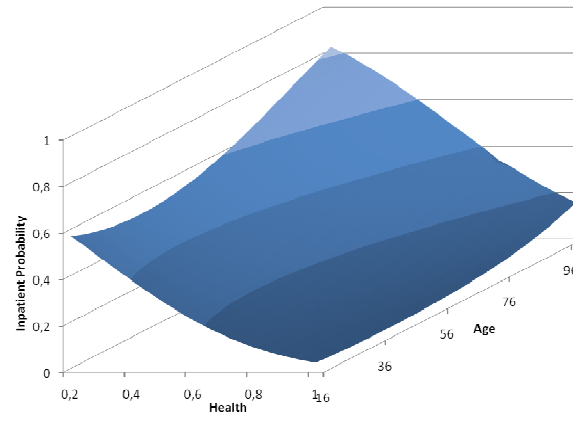


**Figure 3. Effect of need variables on inpatient stay probability**

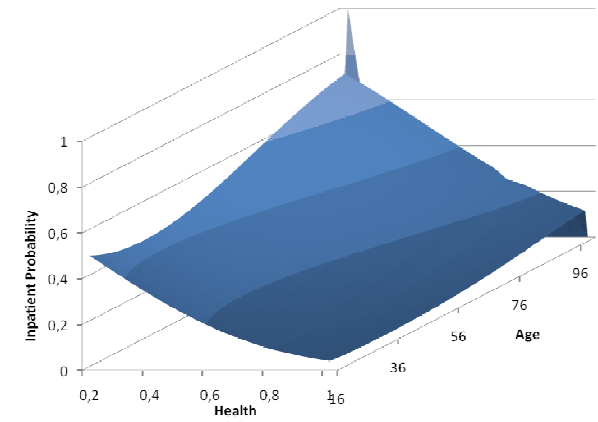
**3(a) All**



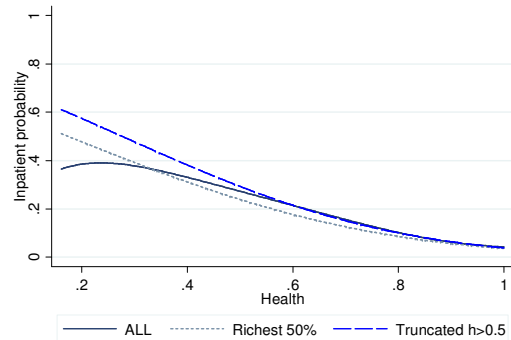
**3(b) Truncated  $h > 0.5$**



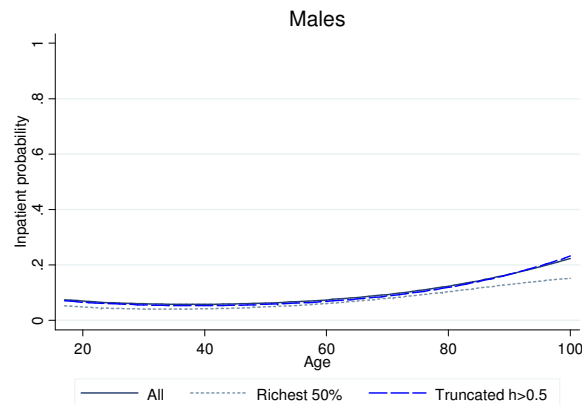
**3(c) Richest 50%**



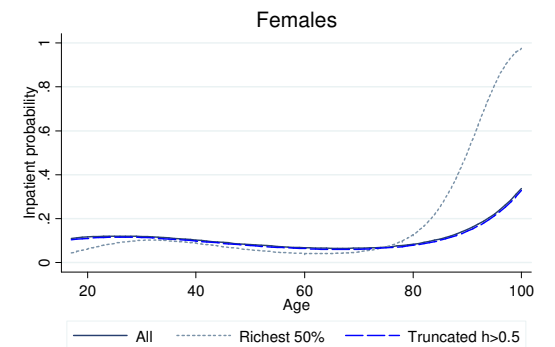
**3(d) Average partial effect of health**



**3(e) Average partial effect of age (Males)**



**3(f) Average partial effect of age (Females)**



**Figure 4. Effect of need variables on outpatient stay probability**

